LETTER TO THE EDITOR

# Contour Mapping and Number of Point Observations

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In a recent issue of the *Journal of Economic Entomology,* Arbogast et al. (2005) published an article upon which we are compelled to comment. The authors state that their article was in part "... to test the validity of contour mapping of trap catch for pest monitoring in warehouses and retail stores." The overall theme of the article was very good, and we share the authors' excitement about the use of pheromone traps for characterization of insect populations and control applications in a spatial context. However, there were problematic aspects of the article that could set a precedent if perpetuated by others in the future, so we felt it necessary to raise our concerns.

Arbogast et al. (2005) released insects at a single point into a shed and then generated contour maps (Figs. 2–4) of interpolated trap captures derived from counts made at four traps located in the same shed. A sample size of four is generally an inadequate number of samples for statistical inference, whether the objective is to measure differences in an analysis of variance or to interpolate spatially dependent samples in a map. Figures 2–4 in Arbogast et al. (2005) are examples of extracting too much information from too few observations. A simple alternative would have been to present the same data as bubble plots with either size, shape, or color of discrete dots indicating the magnitude of trap captures (Bailey and Gatrell 1995, Nansen et al. 2003).

A more subtle problem in Arbogast et al. (2005) is that the contour maps of captures in both sheds and retail pet stores were generated without an a priori analysis of the spatial structure of the data sets. To minimize error of interpolated values and to determine the most appropriate interpolation procedure, the underlying pattern of spatial autocorrelation must first be estimated (Isaaks and Srivastava 1989). There is a large body of literature on spatial statistics of insect counts (Rossi et al. 1992, Liebhold et al. 1993, Brenner et al. 1998, Perry et al. 2002) and spatial interpolation (see Fleischer et al. 1999 for a review) that describes how to use information about the spatial structure of data sets to select the most appropriate interpolation technique. Probably, the most common procedure is to investigate the spatial autocorrelation in a data set by fitting semivariograms or correlograms that characterize the variability among samples over a spectrum of separation distances. These models can then be used in Kriging or one of several other weighted averaging procedures to generate interpolated estimates. Unfortunately, obtaining reliable models of spatial autocorrelation typically requires many samples (e.g., a minimum 50–100 observations) (Journel and Huijbregts 1978, Fortin et al. 1989, Cressie 1993, Liebhold et al. 1993, Tobin 2004), and collecting such large numbers of samples may not be practical in every situation (Arbogast et al. 2005). Arbogast et al. (2005) generated trap capture surfaces by using a multiquadric function (Radial Basis Functions) with default values in the Surfer 8 (Golden Software, Golden, CO) software package. Without any scientific references, the authors state that "The multiquadric method is considered by many to be the best in ability to fit a data set and to produce a smooth surface (Krajewski and Gibbs 2001, Golden Software 2002), and with most small data sets (<250 observations), it produces a good representation of the data (Golden Software 1999)". That Golden Software claims their software produces good representations of data should come as no surprise, but the unqualified endorsement of this method by Arbogast et al. (2005) without any supporting evidence is inconsistent with the vast literature on spatial estimation. Ordinary Kriging is identified in the literature as the Best Linear Unbiased Estimator (Isaaks and Srivastava 1989). There can be many special characteristics of data (e.g., global or zonal anisotropies and highly skewed frequency distributions) that affect whether ordinary Kriging provides the best fit, but this reinforces the concept expressed above that a priori analysis of the actual or expected spatial structure of the data set is needed before performing surface interpolation.

In temporal models of insect population dynamics, it is a standard practice to use independent data sets for model validation and/or to estimate the uncertainty of model predictions. Although validation of map surfaces is less common, we argue that the concept of model validation also should be applied to pest density surface estimation. Typically, the uncertainty of estimated surfaces is spatially variable (maps provide more precise predictions in some areas than in others), and such information on map uncertainty may be critical to utilization of pest density surfaces in pest management programs. One simple approach might be a jackknife validation procedure as described by Krajewski and Gibbs (2001). Jackknife validation procedures are simple, but they are known to slightly overestimate prediction uncertainty (Isaaks and Srivastava 1989). If this is a concern, more complex approaches, such as conditional simulation may be used to characterize uncertainty of spatial predictions (Goovaerts 1997).

In conclusion, we emphasize that although there is tremendous potential for the use of spatially referenced pheromone trap data to spatially characterize insect populations, more care should be given to sta-

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tistical properties before using such data to generate pest abundance surfaces. As Arbogast et al. (2005) point out, maps are effective mechanisms for communicating information to users, but at the same time maps can be very misleading if the information they contain are largely the result of statistical artifacts. With small sample sizes [e.g., $n = 4$ in Arbogast et al. (2005)] users would be well advised to not attempt surface interpolation at all. As an alternative, a simple posting of point observations scaled by size (i.e., bubble plots) or color provides similar information about spatial trends without the complex mathematical procedures or statistical assumptions.

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